

**Comparison of land skin temperature from a land model, remote  
sensing, and in-situ measurement**

Aihui Wang<sup>1\*</sup>, Michael Barlage<sup>2</sup>, Xubin Zeng<sup>3</sup>, Clara Sophie Draper<sup>4</sup>

<sup>1</sup> Nansen-Zhu International Research Centre, Institute of Atmospheric Physics,  
Chinese Academy of Sciences, Beijing, China.

<sup>2</sup> Research Applications Laboratory, National Center for Atmospheric Research,  
Boulder, Colorado, USA

<sup>3</sup> Department of Atmospheric Sciences, The University of Arizona, Tucson, Arizona,  
USA

<sup>4</sup> Global Modeling and Assimilation Office, NASA GSFC, Greenbelt, Maryland, USA  
and GESTAR / Universities Space Research Association, Columbia, Maryland, USA

*Journal of Geophysical Research-Atmospheres*  
(submitted on 10/10/2013)

\* Corresponding author address:

Aihui Wang

Nansen-Zhu International Research Centre

Institute of Atmospheric Physics

Chinese Academy of Sciences

P.O. Box 9804, Beijing 100029

P. R. China

wangaihui@mail.iap.ac.cn

Land skin temperature (Ts) is an important parameter in the energy exchange between the land surface and atmosphere. Here hourly Ts from the Community Land Model Version 4.0, MODIS satellite observations, and in-situ observations in 2003 were compared. Compared with the in-situ observations over four semi-arid stations, both MODIS and modeled Ts show negative biases, but MODIS shows an overall better performance. Global distribution of differences between MODIS and modeled Ts shows diurnal, seasonal, and spatial variations. Over sparsely vegetated areas, the model Ts is generally lower than the MODIS observed Ts during the daytime, while the situation is opposite at nighttime. The revision of roughness length for heat and the constraint of minimum friction velocity from Zeng et al. [2012] bring the modeled Ts closer to MODIS during the day, and have little effect on Ts at night. Five factors contributing to the Ts differences between the model and MODIS are identified, including the difficulty in properly accounting for cloud cover information at the appropriate temporal and spatial resolutions, and uncertainties in surface energy balance computation, atmospheric forcing data, surface emissivity, and MODIS Ts data. These findings have implications for the cross-evaluation of modeled and remotely sensed Ts, as well as the data assimilation of Ts observations into Earth system models.

## 60    **1. Introduction**

61

62        Land skin temperature (Ts) is one of the key variables of the earth system, acting  
63    as the lower boundary of the atmosphere. The difference between Ts and overlying  
64    atmospheric temperature (Ta) helps to determine the partitioning of surface energy  
65    fluxes into sensible and latent heat fluxes [Garratt, 1995; Prigent *et al.*, 2003]. Ts also  
66    controls the amount of heat transfer from the land surface into the soil, and then  
67    indirectly affects thermal states in deep soil. Hence, there is potential to improve land  
68    surface flux forecasts by assimilating Ts observations [e.g., Bosilovich *et al.*, 2007;  
69    Ghent *et al.*, 2010; Reichle *et al.*, 2010; Xu *et al.*, 2011]. Although the importance of  
70    Ts has been recognized, the accuracy of global Ts datasets over land is not well  
71    understood.

72        Land surface models (LSMs) driven by observation-based atmospheric data are  
73    widely used to produce Ts. The upward longwave radiation fluxes simulated by LSMs  
74    combined with downward longwave radiation fluxes and the surface emissivity can be  
75    used to estimate long-term high resolution Ts continuously. Solar radiation is a driving  
76    force of Ts, which is evident in clearly correlated diurnal and seasonal variations. The  
77    magnitude of modeled Ts is affected by surface land cover, soil moisture, and soil  
78    properties (e.g., soil albedo and soil texture). Due to large land surface heterogeneities,  
79    energy fluxes are difficult to simulate accurately in LSMs. Even over a bare ground  
80    grid cell, LSMs still have difficulty in realistically producing skin temperature and  
81    surface fluxes [Chen *et al.*, 2010; Zheng *et al.*, 2012; Zeng *et al.*, 2012]. Efforts have  
82    also been made to improve the simulation of Ts in LSMs. For example, the

83 underestimation of diurnal  $T_s$  variation over the Tibetan Plateau is a notable  
84 deficiency in most LSMs due to the incorrectly parameterized roughness length for  
85 heat ( $z_{oh}$ ). *Yang et al.* [2002] developed a new  $z_{oh}$  formulation from observations at the  
86 Tibetan Plateau to improve surface turbulence flux parameterization over bare soil  
87 surface, which also improved the  $T_s$  simulation in the Noah LSM [*Chen et al.*, 2010].  
88 Based on theoretical arguments and synthesis of previous observational and modeling  
89 efforts, *Zeng et al.* [2012] improved the  $T_s$  diurnal range simulated over bare ground  
90 in two LSMs through  $z_{oh}$  revisions, constraining minimum friction velocity, and  
91 modification of soil thermal conductivity. *Zheng et al.* [2012] adopted a new  
92 vegetation-dependent formulation of momentum and thermal roughness lengths in the  
93 National Center for Environmental Prediction (NCEP) Global Forecast System (GFS),  
94 and substantially reduced the cold forecast bias during the day, which then improved  
95 the brightness temperature in the NCEP data assimilation system.

96       Many previous evaluation and validation studies involving  $T_s$  modeling have  
97 been based on single point station measurements. However,  $T_s$  is not a routinely  
98 measured variable at meteorological stations, and it is only available at a very limited  
99 number of stations with relatively short data records [e.g., *Augustine et al.*, 2000;  
100 *Baldocchi et al.*, 2001]. Satellite observations can produce land surface measurements  
101 over large areas with high spatial resolutions. For example, global clear-sky  $T_s$   
102 products from the Moderate Resolution Imaging Spectra-radiometer [MODIS,  
103 *Salomonson et al.*, 1989] have been available since 2000. The MODIS sensor  
104 provides a quality data source of  $T_s$  for model evaluation from four daily satellite

105 overpasses [e.g., *Ghent et al.*, 2010] and for data assimilation [e.g., *Bosilovich et al.*,  
106 2007; *Reichle et al.*, 2010; *Xu et al.*, 2011].

107 In this study, through comparisons of Ts from the Community Land Model  
108 version 4.0 (CLM4) with both the MODIS (globally) and in-situ station measurements  
109 (at four locations), we test whether the differences between monthly mean Ts from  
110 these three data sources can be used to better identify errors in, and hence make  
111 improvements to, either of the modeled or remotely sensed data sets. At the same time,  
112 in order to improve the global Ts simulation over bare soil surfaces, the new  
113 parameterization schemes in *Zeng et al.* [2012] were implemented into CLM4.0.  
114 Comparing these three data sets is not straightforward, since substantial representative  
115 differences are expected between Ts estimates obtained from in situ sensors, remote  
116 sensors, and land surface models, most notably due to the differences in the typical  
117 spatial resolution of each of these estimates.

118 Section 2 introduces the MODIS Ts, while Section 3 describes the computations  
119 of Ts in CLM4.0 and the modification of parameterizations. Results are presented in  
120 Section 4, and a summary is given in Section 5.

121

## 122 **2. MODIS skin temperature**

123

124 Two MODIS instruments were installed on the NASA Terra and Aqua satellite  
125 platforms, which were launched in December 1999 and May 2002, respectively. Aqua  
126 overpasses around local solar time of 1:30pm (ascending mode) and 1:30am

(descending mode), while Terra is around 10:30am (descending mode) and 10:30pm (ascending mode). The global  $0.05^{\circ} \times 0.05^{\circ}$  spatial resolution monthly MODIS collection 5 Ts data (MODIS product name: MOD11C3/MYD11C3) used in this work were retrieved from the thermal infrared (TIR) bands using the generalized spilt-window algorithm [Wan *et al.*, 2008]. Since the surface TIR signal is difficult to determine with the presence of clouds, the MODIS monthly Ts product includes information on the individual cloud covered days that were used to filter out cloud-contaminated observations when calculating the mean monthly observed (in situ or remotely sensed) Ts.

The accuracy of satellite Ts is affected by surface retrieval techniques, cloud condition, and land surface properties [Wan *et al.*, 2004; 2008], which all significantly constrain the application range of such products. Therefore, evaluation and validation of remote sensing products based on ground-measurement values are important and necessary [e.g., Wan *et al.*, 2002; 2004; 2008; Wang and Liang, 2009; Zheng *et al.*, 2012]. For example, Wan *et al.* [2004] used the observed data over 20 stations to validate the MODIS Ts. Wang and Liang [2009] evaluated the MODIS Ts with six Surface Radiation Budget Monitoring stations [SURFARD, Augustine *et al.*, 2000]. Studies such as these are essential to understanding the application capability and accuracy of satellite observed Ts.

### 3. Skin temperature in CLM4.0

CLM4.0 is the land component of the Community Earth System Model (CESM), and it can also be used as a stand-alone model to simulate the land surface heat and hydrological variables [Lawrence *et al.*, 2012], as used here. Compared with earlier versions of the model, CLM4.0 has several important modifications and has implemented additional components, including updates to soil hydrology, soil thermodynamics, albedo parameters, a carbon–nitrogen biogeochemical model, an urban canyon model, as well as revised soil and snow sub-models [Oleson *et al.*, 2010; Lawrence *et al.*, 2011]. The surface skin temperature  $T_s$  for a model grid box is not explicitly computed in CLM4.0, but it can be derived from the surface incoming ( $LW\downarrow$ ) and outgoing ( $LW\uparrow$ ) longwave radiation combined with surface emissivity ( $\epsilon$ ):

$$\epsilon\sigma T_s^4 = LW\uparrow - LW\downarrow(1 - \epsilon), \quad (1)$$

where  $\sigma=5.67\times 10^8 \text{Wm}^{-2}\text{K}^{-4}$  is the Stefan-Boltzmann constant. In CLM4.0, surface emissivity over non-vegetated surfaces is constant: 0.96 for soil and wetland, and 0.97 for glacier. Over vegetated surfaces, surface emissivity ( $\epsilon_v$ ) is a function of the leaf ( $L$ ) and stem area index ( $S$ ):

$$\epsilon_v = 1 - e^{-(L+S)/\bar{\mu}}, \quad (2)$$

where  $\bar{\mu} = 1$  is the average inverse optical depth for longwave radiation. The grid box in CLM4.0 is a hybrid of different land unit types (e.g., bare soil, vegetation, glacier, wetland, and urban). Over the vegetated part of a grid cell, the vegetation can be described by up to 16 unique vegetation categories [Oleson *et al.*, 2010]. The grid box averaged  $LW\uparrow$  in the model is computed from the areal weighted  $LW\uparrow$  from both vegetated and bare ground areas.

171 It has been widely recognized that  $z_{oh}$  is important in the parameterization of  
 172 surface fluxes [Zeng and Dickinson, 1998; Yang *et al.*, 2002, 2008; Zeng *et al.*, 2012].  
 173 In LSMs,  $z_{oh}$  is usually a function of roughness length of momentum ( $z_{om}$ ) for bare  
 174 surfaces, or proportional to the canopy height for the vegetated surfaces [Zeng and  
 175 Dickinson, 1998; Oleson *et al.*, 2010]. However, using the current  $z_{oh}$  scheme, CLM  
 176 substantially underestimates diurnal variations of Ts, similar to other LSMs [Chen *et*  
 177 *al.*, 2010; Zeng *et al.*, 2012; Zheng *et al.*, 2012]. Through both theoretical analyses and  
 178 data-model comparison, Zeng *et al.* [2012] suggested some revisions for the model  
 179 parameterization schemes that substantially improved Ts simulations over two  
 180 semi-arid sites in both CLM3.5 and the Noah LSMs. Here, we extend those  
 181 modifications to global CLM4.0 simulations, and we simply describe the new  
 182 parameterization schemes.

183 Zeng *et al.* [2012] modified the  $z_{oh}$  formulation

$$184 \quad \ln\left(\frac{z_{om}}{z_{oh}}\right) = a \left(\frac{u_* z_{om}}{\nu}\right)^b \quad (3)$$

185 where  $\nu = 1.5 \times 10^{-5} \text{ m}^2 \text{ s}^{-1}$  is the molecular viscosity,  $b = 0.5$  and  $a = 0.36$ . These  
 186 values are 0.45 and 0.13 in the default CLM4.0, respectively.

187 Another model deficiency is that under stable conditions (usually during  
 188 nighttime) the computed sensible heat is near zero and largely underestimated, which  
 189 leads to the decoupling of atmospheric boundary layer from the land surface [Beljaars  
 190 and Viterbo, 1998]. Zeng *et al.* [2012] also suggested constraining the minimum  
 191 friction velocity under stable condition,

$$192 \quad u_{*min} = 0.07 \frac{\rho_o}{\rho} \left(\frac{z_{om}}{z_{og}}\right)^{0.18} \quad (4)$$



193 where  $\rho$  ( $\rho_0$ ) is the air density at reference (sea) level,  $z_{om}$  is surface roughness length  
194 for momentum; and  $z_{og} = 0.01$  m is the roughness length of bare soil. A similar  
195 method has been widely used in eddy-correlation flux measurements from towers [*Gu*  
196 *et al.*, 2005]. Because air density correlates with the terrain height, equation (4)  
197 implicitly considers the elevation effects in the computation of sensible heat. Equation  
198 (4) is not used in the default CLM4.0.

199 In the modeling experiments presented below, CLM4.0 was run offline at a  
200  $1.9^\circ \times 2.5^\circ$  horizontal resolution driven by an observation-based global atmospheric  
201 forcing dataset [*Qian et al.*, 2006]. Other parameters, such as vegetation parameters  
202 and soil properties, are from the standard model data package [*Oleson et al.*, 2010].  
203 The model was run for 1995-2004, with the multi-year “spun-up” initialization  
204 [*Lawrence et al.*, 2012], and the results in 2003 were analyzed and compared with  
205 both observations and satellites products.

206 Two model experiments were conducted: one with the default model  
207 parameterization referred to as CLM-C, and another with modifications described by  
208 equations (3) and (4) denoted as CLM-N. The hourly outputs of  $LW^\uparrow$  and surface  
209 emissivity combined with  $LW^\downarrow$  in the atmospheric forcing dataset were used to  
210 compute  $T_s$  from equation (1) over global land areas. In order to compare with  
211 MODIS, the modeled  $T_s$  was interpolated to the four MODIS satellite overpass times.

212

## 213 **4. Results**

214

#### 215 **4.1 Comparisons of Ts from CLM4.0, MODIS, and in-situ measurements**

216

217 Ground measurements at four stations with barren-dominant land cover types are  
218 used to compare with both MODIS and CLM4.0 simulations. Based on equation (1),  
219 Ts at each station was computed from the measurements of surface incoming and  
220 emitted LW, combined with surface emissivity (Table 1). Using inverse-  
221 distance-weighted interpolation method, MODIS Ts over each station was  
222 interpolated from four 0.05° closest pixels, and the modeled Ts was also interpolated  
223 from four closest model grid boxes. The monthly mean Ts was computed using only  
224 the days that were observed as clear sky by MODIS. For example, over Desert Rock  
225 at 1:30pm, there were 25 days in July 2003 under clear sky conditions, and the  
226 monthly mean in situ and modeled Ts values were calculated using only those 25  
227 days.

228 Table 2 compares the monthly mean Ts differences at four times over four  
229 stations between MODIS and CLM4.0 simulations versus in-situ observations in July  
230 2003. These stations over dry regions show large diurnal variations. For example, the  
231 monthly averaged Ts differences between 1:30pm and 1:30am under clear sky  
232 conditions from in-situ measurements are 29.9 K, 27.2 K, 17.22 K, and 25.18 K over  
233 Desert Rock, Colorado, Tongyu, and Gaize, respectively. Both MODIS and modeled  
234 Ts show negative mean differences (MDs) compared with the in situ data (i.e., are  
235 cooler than in situ Ts) at most times at all four stations, and most MDs are statistically  
236 significant at 1% level (Table 2). Both CLM-C and CLM-N have large negative MDs

237 (up to -11.41K for CLM-C and -8.91K for CLM-N, both at 1:30pm at Gaize). MODIS  
238 has negative MDs at night, ranging from -1.93K (10:30pm at Tongyu) to -5.21K  
239 (10:30pm at Gaize), while its MDs could be positive or negative during daytime,  
240 ranging from -2.30K (10:30am at Tongyu) to 10.61K (10:30am at Gaize). If the  
241 abnormally high MD at 10:30am at Gaize is excluded, the daytime MODIS MDs are  
242 generally smaller in magnitude than nighttime values.

243       The root mean square difference between the different Ts data sets used here  
244 would be dominated by these large MDs. However, these MD are not necessarily due  
245 to errors in a specific data set, and may be due to representative differences between  
246 them (e.g., differences in the spatial resolution, including potentially the land cover,  
247 between the data sets). Therefore, we compute the standard derivation of differences  
248 (STDd) between model or MODIS results and in situ observations. The STDd is the  
249 root mean square difference between the data sets, once the bias between them has  
250 been removed. Recognizing the different standard deviations of the in situ data (STDo)  
251 between daytime and nighttime, Table 3 shows that the ratios of STDd/STDo vary  
252 from 0.50 to 1.81 for MODIS, 0.20-1.18 for CLM-C, and 0.20-1.33 for CLM-N.  
253 These ratios are on average greatest at 10:30pm for MODIS and at 1:30pm for  
254 CLM-C and CLM-N.

255       Among the 16 MD values in each column of Table 2, 11 (or 10) values from  
256 MODIS are smaller in magnitude than those from CLM-C (or CLM-N). On the other  
257 hand, 11 of the 16 ratios in Table 3 from CLM-C and CLM-N are smaller than those  
258 from MODIS. CLM-N has 15 values smaller in magnitude than CLM-C in Table 2,

259 demonstrating the improvement in CLM-N, while 13 of the 16 ratios in Table 3 are  
260 within 0.02 between CLM-C and CLM-N.

261 While the better performance of MODIS data than model results in terms of  
262 MDs to the in-situ data is expected, it is still surprising to see the much larger MODIS  
263 MDs (in magnitude) in Table 2 than reported in previous studies [*Wan et al.*, 2002,  
264 2004, 2008]. For example, *Wan et al.* [2004] indicated that the Ts biases of MODIS  
265 from station observations are within 1 K. A potential reason is that previous validation  
266 studies used the MODIS Ts data at the highest resolution (1 km) under clear-sky  
267 conditions while we use the MODIS data at  $0.05^\circ$  (~5 km) grid cells for global studies.  
268 In general, our 5 km MODIS Ts data used in Tables 2 and 3 may contain partially  
269 cloudy conditions and hence contain more days of data in a given month. For instance,  
270 at 10:30pm at Gaize, while the MODIS MD is -5.21 K in July, it is less than 1.45 K in  
271 magnitude for 25% of the days. On the other hand, at 10:30am at Gaize, the MODIS  
272 MD is 10.61 K in July, and such a large positive bias indicates the deficiency of the  
273 MODIS data at this time over this high altitude location.

274 It is also interesting to note that MODIS from Aqua (1:30am/1:30pm) performs  
275 better than that from Terra (10:30am/10:30pm) compared with in situ measurements.  
276 For nighttime MDs (at 1:30am and 10:30pm) and daytime values (at 1:30pm and  
277 10:30am) in Table 2, Aqua (or Terra) gives smaller MDs in magnitude seven (or just  
278 one) times. Similarly, Aqua (or Terra) gives smaller ratios seven (or just one) times in  
279 Table 3.

280 The MDs of CLM-N in Table 2 are also much larger than those reported in *Zeng*

281 *et al.* [2012] at both Desert Rock and Gaize sites. The improvement of daytime Ts in  
 282 CLM-N over CLM-C is substantial in *Zeng et al.* [2012], while it is more moderate in  
 283 Table 2. These different results can be reconciled along several different lines. In the  
 284 results presented here, the model was run globally at coarse resolution ( $1.9^{\circ} \times 2.5^{\circ}$ )  
 285 where only 65% of the grid box near Desert Rock was of the bare soil, while in *Zeng*  
 286 *et al.* [2012] CLM4.0 was run at a single point with 100% bare soil fraction at this site.  
 287 Furthermore, the atmospheric forcing data, particularly air temperature (which is  
 288 related to elevation) and downward solar radiation (SWd), are very different between  
 289 our simulations based on the *Qian et al.* [2006] data, and the in situ measurements  
 290 used in *Zeng et al.* [2012]. For instance, Table 2 shows that 12 of the 16 air  
 291 temperature differences between *Qian et al.* [2006] and in situ data are less than -3 K,  
 292 and all SWd differences are negative. While some of these differences in the  
 293 atmospheric forcing are due to errors in each data set, the large difference in spatial  
 294 resolution of each atmospheric data set would also introduce some differences.

295

## 296 **4.2 Evaluation of the CLM4.0 modeling with MODIS Ts**

297

298 Using the  $0.05^{\circ}$  MODIS Ts data to evaluate global model output is not  
 299 straightforward, and involves several steps. First, at each satellite overpass time (four  
 300 times daily), MODIS monthly Ts data are spatially averaged within each CLM4.0 grid  
 301 box with the requirement that at least 20% of the model grid box is defined as land in  
 302 MODIS. Each  $1.9^{\circ} \times 2.5^{\circ}$  CLM4.0 grid box potentially includes 1900  $0.05^{\circ} \times 0.05^{\circ}$

MODIS observations. Another important consideration is the potential for cloud contamination adversely affecting MODIS Ts. Scarino et al. (2013) found increased agreement between remotely sensed and in-situ Ts with decreasing cloud cover. The number of MODIS grid cells observed as clear-sky in each model grid box varies with month and location. Hence, we also calculate the clear sky fraction (CF) as the percentage of MODIS grid cells within each CLM4.0 grid box that are declared as clear on a given day. The CF values for an individual day averaged over global land (excluding the Antarctic) vary from 45-60%, and the monthly mean values in July are a little bit larger than in January.

Figure 1 shows the distribution of global CLM4.0 grid boxes based on the monthly mean of MODIS daily CF, binned into 10% intervals from 0-100%, at each satellite overpass time in January and July 2003, respectively. The clear-sky fraction is greater than 90% for ~25% of the model grid boxes in January and ~28% in July, primarily over semi-arid and arid regions, e.g., northern Africa, Middle East, western China, western and central Australia, and southwestern United States. CF is less than 10% for ~25% of model grid boxes in January and ~20% in July, primarily over tropical rainforests such as the Amazonia, equatorial Africa, and south-eastern Asia. The higher percentages of model grid boxes at the low CF bin in January (Figure 1a) than in July (Figure 1b) are related to the more extensive cloud cover in the wet season (including January) over tropical rainforests. For the four overpass times, the percentage of model grid boxes with  $CF < 10\%$  is highest at 1:30am, consistent with the nighttime precipitation maximum over rainforests [Angelis et al., 2004]. The

percentage of model grid boxes for  $CF > 90\%$  in July (Figure 1b) is higher during the day (at 10:30am and 1:30pm) than at night (at 1:30am and 10:30pm), probably because of the higher relative humidity at night over dry regions. For CF between 10-90%, the percentage of model grid boxes varies from 8.7-5.1%, and in the same CF bin they change little with satellite overpass times.

Since MODIS Ts observations are for clear-sky conditions only, the model Ts must also be screened for cloudy conditions before being compared to MODIS observed values. This screening is complicated by the spatial and temporal aggregation between the observed Ts and monthly mean modeled values. To address this we first bin the daily MODIS CF values for all model grid cells into 10% intervals from 0-100%. We then calculate the monthly model Ts for each bin from hourly CLM4.0 Ts from every day of the month. That is, for different daily CF bins, the number of grid boxes used to compute the monthly mean is different. For example, in July over northern hemisphere (NH), about 75% of the model land grid boxes were used in the computation of monthly mean values at 1:30pm for  $CF > 50\%$ , while only about 50% of the model land grid boxes were used for  $CF > 90\%$ . Furthermore, we require that the daily MODIS Ts data at each overpass time are available for at least 10 (clear) days in a month for the calculation of the monthly mean. Using these criteria, it is found that the MD between the modeled and remotely sensed Ts (i.e., mean CLM minus MODIS Ts) generally decrease with increasing CF values over both hemispheres. For instance, at 1:30 pm in July 2003, the MD over Southern Hemisphere (SH) land areas varies from 0.59 K (for  $CF < 10\%$ ) to -0.32 K (for

347 CF>90%), while over NH, it varies from 1.55 K (for CF<10%) to 1.04 K (for  
348 CF>90%).

349 For CF > 50%, Figure 2 shows the spatial distribution of the differences between  
350 CLM-C and MODIS Ts at four satellite overpass times averaged in July 2003,  
351 respectively. The Ts biases display large spatial and diurnal variations, and the  
352 magnitudes of differences are substantial over some regions. At daytime, areas with  
353 negative biases are mainly located at midlatitude arid and semi-arid regions, while at  
354 nighttime positive biases are dominant over most of land areas. The global mean  
355 difference in NH varies from -2.17 K (at 10:30am) to 4.33 K (10:30 pm), while in SH  
356 it varies between -2.40 K (10:30am) to 4.09 K (10:30pm). At 1:30pm, the mean  
357 differences over two hemispheres are smallest in magnitude among all four times,  
358 with values of 0.07 K in SH and 1.25 K in NH, respectively. *Wan et al.* [2004] also  
359 found that MODIS Ts at 1:30 pm is closer to in-situ measurements, and suggested  
360 that Ts at 1:30pm would be more suitable for climate change studies since the  
361 1:30pm local solar time is closer to the maximum temperature of the land surface.

362 The mean differences between CLM-C and MODIS in January are on average  
363 larger in magnitude than those in July. For instance, the mean difference is 5.80 K in  
364 SH (versus 4.09 K in July in Figure 2). At 1:30pm, the mean difference over SH of  
365 0.18 K is also the smallest in magnitude among all four times over both hemispheres.  
366 In January, due to the snow existence over northern high latitudes (and some  
367 midlatitude regions), satellite-retrieved surface products might contain large errors,  
368 and the comparison of CLM4.0 and MODIS data may not be appropriate.



369

### 370 **4.3 Performance of the CLM4.0 with Eqs. (3) and (4)**

371

372 As mentioned in *Zeng et al.* [2012], equation (3) primarily increases the daytime  
373 Ts with a negligible effect on nighttime Ts. Equation (4) slightly increases Ts under  
374 very weak wind and stable conditions at night. Figure 3 shows the Ts differences  
375 between CLM-N and CLM-C with respect to bare ground fractions in 5% intervals.  
376 Indeed the Ts from CLM-N is overall larger than that from CLM-C, and their  
377 differences increase with the bare soil fraction. The difference is more pronounced in  
378 the day time than at night and in the warm month than in the cold month. The largest  
379 difference is at 1:30 pm in January over SH, and the values are up to 6 K over the  
380 totally bare covered regions.

381 Therefore, we mainly focus on the evaluation of equations (3) and (4) with  
382 MODIS at day time over regions where bare ground fraction is greater than 30%.  
383 These regions include most of semi-arid and arid areas, such as northern Africa,  
384 Middle East, northwest China, Tibetan Plateau, central and western Australia, and  
385 small areas of southwestern United States.

386 Figures 4 and 5 plot the global distribution of Ts differences between CLM-N  
387 and CLM-C, and between CLM-C and MODIS at day times. The Ts differences vary  
388 seasonally and spatially, and they are greater in July than in January. The Ts  
389 differences between CLM-C and MODIS are generally negative over most regions,  
390 and they are less than -8 K (i.e., greater than 8K in magnitude) at 10:30am over part

391 of the northern China, Arabian Peninsula, and Sahara Desert (Figures 4c and 5c). The  
392 differences between CLM-N and CLM-C are positive over most regions, and CLM-N  
393 overall reduces the cold biases compared to MODIS Ts of CLM-C at day time shown  
394 in Figure 4.

395 Table 4 summarizes the hemisphere averaged results from Figures 4 and 5. The  
396 differences are all negative except at 1:30pm in July over NH between CLM-N and  
397 MODIS. This issue will be further discussed in section 4.4. The mean differences  
398 between CLM-N and MODIS are generally smaller than those between CLM-C and  
399 MODIS, suggesting that equations (3) and (4) reduce the cold bias of CLM-C.

400

#### 401 **4.4. Possible reasons for Ts biases between CLM4.0 and MODIS**

402

403 The large differences between the Ts estimates from CLM4.0 and MODIS could  
404 be due to errors in either data set, or representative differences between them. With no  
405 independent measure of Ts at global scales, it is difficult to definitively attribute a  
406 cause to the large mean differences obtained above. However, cross-referencing these  
407 mean differences with independent information on the accuracy of each data set can  
408 help to confirm known problems in each data source.

409 For the large Ts differences in Figure 4 and Table 4, we can identify several  
410 possible reasons. First, there are deficiencies in the energy balance computation in  
411 CLM4.0. In the past few years, many efforts have been made to reduce such  
412 deficiencies [Zeng and Wang, 2007; Wang and Zeng, 2009; Zeng et al., 2012].

413 Equations (3) and (4) from *Zeng et al.* [2012] are also among such efforts. Indeed  
414 Table 4 shows that these revisions reduce the cold bias of CLM-C (compared to  
415 MODIS).

416 Second, there are deficiencies in the atmospheric forcing data [e.g., *Guo et al.*,  
417 2006; *Wang and Zeng*, 2011]. For global land areas, accurate atmospheric forcing  
418 data are not available. The current global forcing data sets are usually based on  
419 reanalysis datasets with bias correction by limited in-situ or remote-sensed  
420 observations [e.g., *Qian et al.*, 2006; *Sheffield et al.*, 2006]. *Wang and Zeng* [2011]  
421 found that the precipitation and air temperature in the atmosphere forcing data of  
422 *Qian et al.* [2006] used in CLM4.0 are largely biased compared with in situ  
423 observation-based data over China, and these biases affect the modeled soil hydrology  
424 variables. As mentioned earlier, there are also large biases, compare to in situ data, in  
425 the air temperature and downward solar radiation in the forcing data of *Qian et al.*  
426 [2006] (Table 2), which are likely in part due to differences in spatial resolution and  
427 elevation.

428 Furthermore, the Ts differences between CLM4.0 and MODIS are partially  
429 affected by the different treatment of surface emissivity in the Ts computation in  
430 equation (1). Surface emissivity is constant over bare soil and is a simple function of  
431 vegetation leaf area index in CLM4.0 (equation 2), while the MODIS surface  
432 emissivity is estimated from land cover type in each 0.05° pixel through MODIS  
433 thermal infrared (TIR) bands and a classification –based emissivity model [*Snyder et*  
434 *al.* 1998]. *Wan et al.* [2004] pointed out that errors in the classification –based

emissivity may be larger over semi-arid and arid regions due to larger temporal and spatial variations. Surface emissivity over bare soil is affected by many factors (e.g., surface chemical composition) and the wavelength at which the emissivity is measured [Van De Griend and Owe, 1993; Jin and Liang, 2006]. In particular, Jin and Liang [2006] found that assuming a constant surface emissivity over bare soil would strongly affect Ts and sensible heat fluxes over desert.

As mentioned earlier, CLM4.0 results represent the effective Ts over all land cover types present in each 1.9°x2.5° grid box, while the MODIS monthly Ts is computed from only the clear-sky 0.05° pixels in each grid box. We only used the days with MODIS clear sky fraction greater than 50% in each model grid box when we computed the monthly average of the modeled Ts in Figures 3-5. This means that we essentially compared the clear-sky MODIS Ts with model Ts under partially cloudy conditions. Since clouds decrease downward solar radiation, this would introduce a cold bias of daytime Ts between CLM4.0 and MODIS. On the other hand, if we only consider days with MODIS clear-sky fraction > 90% in each 1.9°x2.5° box, then the percentage of grid boxes would be about 30% in July and less than 25% in January (Figure 1), and the number of such days in each grid box would be also very limited.

Besides the model-observation inconsistencies and model forcing data deficiencies, there are also MODIS Ts deficiencies. As shown in Figure 4d and Table 4 at 1:30pm in July, the substantial positive biases between CLM-C and MODIS in northeastern Africa are opposite to those over other regions of the Sahara Desert. To

457 further explore this issue, we selected two grid boxes (centered around 29°N/23°E and  
458 29°N/10°W) in northeastern Africa. Figure 6 shows that both CLM-C and MODIS  
459 have strong diurnal variations at both grid boxes. Because both boxes are located at  
460 the same latitude over the Sahara Desert with bare soil fraction greater than 90%, the  
461 differences of Ts (including its diurnal cycle) between the two boxes are expected to  
462 be smooth with time. This is indeed the case for CLM-C (Figure 6b). However, the  
463 MODIS Ts differences between two grid boxes show much more pronounced diurnal  
464 variations which also differ from month to month. Therefore, the abnormal positive  
465 Ts differences between CLM4.0 and MODIS over northeastern Africa are thought to  
466 be caused by MODIS Ts warm biases, which in turn may be related to MODIS  
467 surface emissivity deficiencies over this area [e.g., *Wan et al.*, 2004]. A similar  
468 situation to Figure 6 was also found in the Amazon rainforest (Figure not shown), and  
469 the MODIS Ts bias there may be related to the difficulty in identifying clear-sky  
470 pixels.

471

## 472 **5. Summary and further discussions**

473

474 Land skin temperature (Ts) is one of the important parameters in the energy  
475 exchange between the land surface and atmosphere. Lack of global long-term in-situ  
476 Ts observations is a barrier to understanding the earth system. Land surface models  
477 and satellites provide two alternative ways to produce Ts. Various data sources,  
478 however, contain deficiencies and limitations, and their comparison would provide

479 some insights for the data developers and users.

480 In this study, Ts from MODIS, in-situ station measurements, and the Community  
481 Land Model version 4 (CLM4.0) simulations in 2003 were compared. Two  
482 modifications (i.e., equations (3) and (4)) are also implemented into CLM4.0. Hourly  
483 outputs of surface emitted longwave radiation combined with the surface downward  
484 thermal radiation fluxes are used to compute Ts over global land areas. MODIS Ts is  
485 only available during cloud-free conditions, while modeled Ts is the averaged-value  
486 of whole grid box regardless of cloud cover. Therefore, in the comparison of modeled  
487 and MODIS Ts, the MODIS clear-sky information is used to make the comparison  
488 more consistent.

489 Results show that both MODIS and modeled Ts datasets can capture the diurnal  
490 variation of Ts at four station locations, but also display distinct biases compared to  
491 the in situ data. Both MODIS and modeled Ts show significant negative mean  
492 differences at most times in July 2003, and the mean differences are statistically  
493 significant at the 1% level. The magnitude of biases varies by station and time. The  
494 MODIS Ts is generally closer to station observations than the model simulations are.

495 Under the 50% MODIS clear-sky fraction conditions, global comparisons  
496 between the MODIS and modeled Ts also show that their mean differences vary  
497 spatially and seasonally. Over land areas the mean differences are mostly negative  
498 during the day (i.e., model has a cold bias compared to MODIS) and positive at night.  
499 The modified CLM4.0 reduces this cold bias in the daytime over bare ground  
500 dominated regions.

501        Comparison of (TIR) remotely sensed and modeled Ts requires the consistent  
502        treatment of cloudy conditions between the two data sets, including in the calculation  
503        of spatially and/or temporally aggregated values. Furthermore, comparison of MODIS  
504        and modeled Ts can help to identify deficiencies in MODIS Ts over some regions,  
505        such as the Sahara Desert.

506        While the monthly mean time scale of this study is not directly relevant to most  
507        data assimilation applications, this work has some obvious implications for the  
508        assimilation of remotely sensed Ts into Earth system models. Most notably, the large  
509        biases between modeled and remotely sensed Ts are not unique to this study [e.g.,  
510        *Ghent et al.*, 2010; *Scarino et al.*, 2013], and must be addressed before Ts data can be  
511        assimilated (since standard data assimilation techniques are contingent on the  
512        observations and the model being bias free). This is usually achieved by rescaling the  
513        observations to be consistent with the model Ts prior to assimilation [e.g., *Ghent et al.*,  
514        2010; *Reichle et al.*, 2010]. Additionally, the need to carefully account for cloudy  
515        conditions when comparing modeled and observed Ts also applies to the assimilation  
516        of (clear-sky) Ts observations, particularly where those observations are spatially  
517        aggregated before assimilation.

518        This work is a first step toward evaluating LSM outputs using the remotely  
519        sensed Ts products over global land areas, and will provide useful guidance for future  
520        studies. Our comparison between the CLM4.0 modeled and MODIS observed Ts  
521        established the monthly mean differences between them, which helped to identify  
522        some deficiencies in the CLM4.0 model.

523

524 Acknowledgments:

525       The work of AW was supported by the Department of Science and Technology  
526 of China under Grants 2010CB428403 and the National Science Foundation of China  
527 under Grant 41275110, the work of XZ was supported by the National Science  
528 Foundation (AGS-0944101) and NASA (NNX09A021G), while the work of MB was  
529 supported by NOAA (NA13NES4400003), and the work of CSD was supported by  
530 the NASA Modeling, Analysis, and Prediction Program, and the National Climate  
531 Assessment.

532



533 References:

534

535 Angelis, C. F., G. R. McGregor, C. Kidd (2004), Diurnal cycle of rainfall over the

536 Brazilian Amazon, *Clim. Res.*, 26, 139-149.

537 Augustine, J. A., J. J. DeLuisi, and C. N. Long (2000), SURFRAD—A national

538 surface radiation budget network for atmospheric research, *Bull. Am. Meteorol.*

539 *Soc.*, **81**, 2341-2357, doi:10.1175/1520-0477.

540 Baldocchi, D. et al. (2001), FLUXNET: A new tool to study the temporal and spatial

541 variability of ecosystem-scale carbon dioxide, water vapor, and energy flux

542 densities, *Bull. Amer. Meteor. Soc.*, 82, 2415-2434.

543 Bosilovich, M., J. Radakovich, A. da Silva, R. Todling, and F. Verter (2007), Skin

544 temperature analysis and bias correction in a coupled land-atmosphere data

545 assimilation system, *J. Meteorol. Soc. Jap.*, 85A, 205-228.

546 Chen, Y., K. Yang, D. Zhou, J. Qin, and X. Guo (2010), Improving the Noah land

547 surface model in arid regions with an appropriate parameterization of the thermal

548 roughness length, *J. Hydrometeorol.*, 11, 995-1006.

549 Garratt, J. R. (1995), Observed screen (air) and GCM surface/screen temperatures:

550 Implications for outgoing longwave fluxes at the surface, *J. Clim.*, 8, 1360-1368.

551 Ghent, D., J. Kaduk, J. Remedios, J. Ardö, and H. Balzter (2010), Assimilation of land

552 surface temperature into the land surface model JULES with an ensemble

553 Kalman filter, *J. Geophys. Res.*, 115, D19112, doi:10.1029/2010JD014392

554 Gu, L., et al. (2005), Objective threshold determination for nighttime eddy flux

555 filtering, *Agric. For. Meteorol.*, 128, 179-197.

556 Guo, Z., P. A. Dirmeyer, Z.-Z. Hu, X. Gao, and M. Zhao (2006), Evaluation of the  
 557 second global soil wetness project soil moisture simulations: 2. Sensitivity to  
 558 external meteorological forcing, *J. Geophys. Res.*, 111, D22S03,  
 559 doi:10.1029/2006JD007845

560 Lawrence, D., et al. (2011), Parameterization improvements and functional and  
 561 structural advances in version 4 of the Community Land Model, *J. Adv. Model.*  
 562 *Earth Syst.*, 3, doi:10.1029/2011MS000045.

563 Lawrence, D., et al. (2012), The CCSM4 land simulation, 1850–2005: assessment of  
 564 surface climate and new Capabilities, *J. Clim.*, 25, 2240-2260.

565 Jin, M. and S. Liang (2006), An improved land surface emissivity parameter for Land  
 566 Surface Models using global remote sensing observations, *J. Clim.*, 19,  
 567 2867-2881.

568 Oleson, K., et al. (2010), Technical description of version 4.0 of the Community Land  
 569 Model, NCAR Tech. Note NCAR/TN-4781STR, 257 pp.

570 Prigent, C., F. Aires, and W. B. Rossow (2003), Land surface skin temperatures from a  
 571 combined analysis of microwave and infrared satellite observations for an  
 572 all-weather evaluation of the differences between air and skin temperatures, *J.*  
 573 *Geophys. Res.*, 108(D10), 4310, doi:10.1029/2002JD002301.

574 Qian, T., A. Dai, K. E. Trenberth, and K. W. Oleson (2006), Simulation of global land  
 575 surface conditions from 1948 to 2002: Part I: Forcing data and evaluations, *J.*  
 576 *Hydrometeorol.*, 7, 953–975.

577 Reichle, R. H., S. V. Kumar, S. P. P. Mahanama, R. D. Koster, and Q. Liu (2010),

578 Assimilation of satellite-derived skin temperature observations into land surface  
579 models, *J. Hydrometeorol.*, *11*, 1103-1122.

580 Salomonson, V. V., W. L. Barnes, P. W. Maymon, H. Montgomery, and H. Ostrow  
581 (1989), MODIS: Advanced facility instrument for studies of the Earth as a  
582 system, *IEEE Trans. Geosci. Remote Sens.*, *27*, 145-153, doi:10.1109/36.20292.

583 Scarino, B., P. Minnis, R. Palikonda, R. H. Reichle, D. Morstad, C. Yost, B. Shan, and  
584 Q. Liu (2013), Retrieving clear-sky surface skin temperature for numerical  
585 weather prediction applications from geostationary satellite data, *Remote Sens.*, *5*,  
586 342-366, doi:10.3390/rs5010342.

587 Sheffield, J., G. Goteti, and E. F. Wood (2006), Development of a 50-year  
588 high-resolution global dataset of meteorological forcings for land surface  
589 modeling, *J. Clim.*, *19*, 3088-3111.

590 Snyder, W. C., Z. Wan, Y. Zhang, and Y.-Z. Feng (1998), Classification - based  
591 emissivity for land surface temperature measurement from space, *Int. J. Remote*  
592 *Sens.*, *19*, 2753-2774, doi:10.1080/014311698214497.

593 Van De Griend, A. A., and M. Owe (1993), On the relationship between thermal  
594 emissivity and the normalized difference vegetation index for nature surfaces, *Int.*  
595 *J. Remote Sens.*, *14*, 1119-1131.

596 Wan, Z., Y. Zhang, Q. Zhang, and Z.-L. Li (2002), Validation of the land surface  
597 temperature products retrieved from Terra Moderate Resolution Imaging  
598 pectroradiometer data, *Remote Sens. Environ.*, *83*, 163- 180,  
599 doi:10.1016/S0034-4257(02)00093-7.

600 Wan, Z., Y. Zhang, Q. Zhang, and Z.-L. Li (2004), Quality assessment and validation  
601 of the MODIS global land surface temperature, *Int. J. Remote Sens.*, 25(1), 261–  
602 274, doi:10.1080/0143116031000116417.

603 Wan, Z., and Z.-L. Li (2008), Radiance-based validation of the V5 MODIS  
604 land-surface temperature product, *Int. J. Remote Sens.*, 29, 5373–5395,  
605 doi:10.1080/01431160802036565.

606 Wang A. and X. Zeng (2009), Improving the treatment of vertical snow burial fraction  
607 over short vegetation in the NCAR CLM3, *Adv. Atmo. Sci.*, 26, 877-886.

608 Wang, A., and X. Zeng (2011), Sensitivities of terrestrial water cycle simulations to  
609 the variations of precipitation and air temperature in China, *J. Geophys. Res.*, 116,  
610 D02107, doi:10.1029/2010JD014659.

611 Wang, K. and S. Liang (2009), Evaluation of ASTER and MODIS land surface  
612 temperature and emissivity products using long-term surface longwave radiation  
613 observation at SURFRAD sites, *Remote Sens. Environ.*, 113, 1556-1565.

614 Xu, T., S. Liu, S. Liang, and J. Qin (2011), Improving predictions of water and heat  
615 fluxes by assimilating MODIS, *J. Hydrometeorol.*, 12, 227-244.

616 Yang, K., T. Koike, H. Fujii, K. Tamagawa, and N. Hirose (2002), Improvement of  
617 surface flux parameterizations with a turbulence - related length, *Q. J. R.*  
618 *Meteorol. Soc.*, 128, 2073 – 2087, doi:10.1256/003590002320603548.

619 Yang, K., et al. (2008), Turbulent flux transfer over bare soil surfaces: Characteristics  
620 and parameterization, *J. Appl. Meteorol. Clim.*, **40**, 276-290.

621 Zeng X., and A. Wang (2007), Consistent parameterization of above-canopy

622       turbulence for sparse and dense canopies in land models, *J. Hydrometeorol.*, 8,  
623       730-737.

624   Zeng, X. and R. E. Dickinson (1998), Effect of surface sublayer on surface skin  
625       temperature and fluxes, *J. Clim.*, 11, 537-550.

626   Zeng, X., Z. Wang, and A. Wang (2012), Surface skin temperature and the interplay  
627       between sensible and ground heat fluxes over arid regions, *J. Hydrometeorol.*, 13,  
628       1359-1370.

629   Zheng, W., H. Wei, Z. Wang, X. Zeng, J. Meng, M. Ek, K. Mitchell, and J. Derber  
630       (2012), Improvement of daytime land surface skin temperature over arid regions  
631       in the NCEP GFS model and its impact on satellite data assimilation, *J. Geophys.*  
632       *Res.*, 117, D06117, doi:10.1029/2011JD015901.  
633

634 Table captions

635

636 Table 1. Information of four stations used in this study.

637

638 Table 2. Monthly mean Ts differences between MODIS, CLM-C and CLM-N versus  
639 in situ observations over four stations at four satellite overpass times in July, 2003.

640 Only the values under clear-sky conditions as indicated by the MODIS Ts data are  
641 used. The corresponding biases between Tair and downward shortwave radiation  
642 (SWdn) between CLM forcing and in-situ measurements are also shown in the last  
643 two columns. Biases that are statistically significant at the 1% level based on the  
644 Student's t-test are indicated in bold.

645

646 Table 3. Ratios of the standard deviations (STD) of Ts differences (STDd) between  
647 model or MODIS results and in situ observations to the STD of in-situ observations  
648 (STDo) over four stations at four satellite overpass times in July 2003.

649

650 Table 4. Monthly Ts differences (K) averaged over Northern Hemisphere (NH) and  
651 Southern Hemisphere (SH) land grid cells between CLM-C and MODIS, and between  
652 CLM-N and MODIS in January and July 2003, respectively. At each MODIS satellite  
653 overpass time, only the grid cells meeting two criteria are used to compute monthly Ts  
654 in CLM: a) bare fraction (BF) is greater than 30%; and b) MODIS clear-sky fraction  
655 (CF) is greater than 50% for at least 10 days in the month.

656

657

658 Figure captions

659

660 Figure 1. CLM4.0 grid box number percentages over land (excluding the Antarctic)  
661 versus clear-sky percentages using results from each overpass for each day for the  
662 whole month in January and July, 2003.

663

664 Figure 2. Monthly Ts differences between CLM-C and MODIS at four overpass times  
665 in July 2003. At each overpass time, CLM-C monthly Ts values are computed only for  
666 grid boxes with MODIS clear-sky fraction > 50% for at least 10 days in the month.  
667 The areal weighted values over each hemispheric land areas are also shown in the  
668 figure.

669

670 Figure 3. Hemisphere mean Ts differences between CLM-N and CLM-C versus bare  
671 soil fraction in 5% intervals at four satellite overpass times averaged in January and  
672 July 2003. NH and SH denote Northern and Southern Hemispheres, respectively.

673

674 Figure 4. Global distribution of Ts differences between CLM-N and CLM-C at a)  
675 10:30am; b) 1:30pm, and between CLM-C and MODIS at c) 10:30am; d) 1:30pm in  
676 July 2003. At each satellite overpass time, monthly Ts is computed over grid boxes  
677 with bare soil fraction greater than 30% and MODIS clear-sky fraction greater than 50%  
678 for at least 10 days in the month.

679

680 Figure 5. Similar as Figure 4 but for January 2003.

681

682 Figure 6. a) Monthly averaged Ts at two grid boxes at the four satellite overpass times  
683 and b) the Ts differences between these two boxes (centered around 29°N/23°E, and  
684 29°N/10°W) from CLM-C and MODIS. Both boxes are located in the Sahara Desert  
685 with bare soil fraction greater than 90%.

686

687 Table 1. Information of four stations used in this study.

688

Station name	Location		Surface emissivity	Data sources	References
	Lat(°N)	Lon(°E)			
Desert Rock	36.62	-116.02	0.96	SURFRAD	<i>Augustine et al. 2000</i>
Colorado	40.13	-105.24	0.98	SURFRAD	<i>Augustine et al. 2000</i>
Tongyu	44.41	122.87	0.96	CEOP	<i>Yang et al. 2008</i>
Gaize	32.3	84.5	0.91	CEOP	<i>Chen et al. 2010</i>

689



690 Table 2. Monthly mean Ts differences between MODIS, CLM-C and CLM-N versus  
691 in situ observations over four stations at four satellite overpass times in July 2003.  
692 Only the values under clear-sky conditions as indicated by the MODIS Ts data are  
693 used. The corresponding biases between Tair and downward shortwave radiation  
694 (SWdn) between CLM forcing and in-situ measurements are also shown in the last  
695 two columns. Biases that are statistically significant at the 1% level based on the  
696 Student's t-test are indicated in bold.  
697

		Ts diff. (K)			Tair diff. (K)	SWdn diff. (W/m <sup>2</sup> )
		MODIS	CLM-C	CLM-N		
Desert	1:30a	<b>-4.14</b>	<b>-6.47</b>	<b>-5.69</b>	<b>-10.31</b>	0.
	10:30a	<b>2.23</b>	<b>-3.79</b>	-1.85	<b>-3.02</b>	<b>-142.46</b>
Rock	1:30p	<b>-1.30</b>	<b>-4.35</b>	-1.61	<b>-1.75</b>	<b>-154.26</b>
	10:30p	<b>-4.17</b>	<b>-5.72</b>	<b>-4.92</b>	<b>-8.47</b>	0
Colorado	1:30a	<b>-4.07</b>	<b>-5.22</b>	<b>-4.78</b>	<b>-9.98</b>	0
	10:30a	<b>2.27</b>	<b>-7.02</b>	<b>-6.83</b>	<b>-4.34</b>	<b>-207.06</b>
	1:30p	<b>-1.26</b>	<b>-5.95</b>	<b>-5.53</b>	<b>-3.65</b>	-77.63
	10:30p	<b>-4.26</b>	<b>-5.07</b>	<b>-4.55</b>	<b>-7.99</b>	0
	1:30a	-2.55	-0.36	-0.15	-0.87	0
Tongyu	10:30a	-2.30	<b>-5.31</b>	-4.86	<b>-4.15</b>	<b>-215.74</b>
	1:30p	-1.15	-2.43	-2.03	-1.94	-78.54
	10:30p	<b>-1.93</b>	0.19	0.40	0.71	0
	1:30a	<b>-3.51</b>	<b>-2.27</b>	-1.23	<b>-3.76</b>	0
Gaize	10:30a	<b>10.61</b>	<b>-8.76</b>	<b>-7.06</b>	<b>-9.25</b>	<b>-215.91</b>
	1:30p	<b>1.92</b>	<b>-11.41</b>	<b>-8.91</b>	<b>-7.79</b>	<b>-186.43</b>
	10:30p	<b>-5.21</b>	<b>-2.83</b>	-1.59	<b>-3.99</b>	0

698

699

700 Table 3. Ratios of the standard deviations (STD) of Ts differences (STDd) between  
701 model or MODIS results and in situ observations to the STD of in-situ observations  
702 (STDo) over four stations at four satellite overpass times in July 2003.

		STDd/STDo		
		MODIS	CLM-C	CLM-N
Desert	1:30am	0.50	0.53	0.55
	10:30am	1.05	0.79	0.85
	1:30pm	0.96	1.18	1.33
Rock	10:30pm	1.56	0.56	0.58
	1:30am	0.82	0.91	0.91
	10:30am	1.06	0.95	0.95
Colorado	1:30pm	0.70	0.97	0.98
	10:30pm	1.05	0.83	0.83
	1:30am	0.62	0.20	0.20
Tongyu	10:30am	1.21	1.02	1.02
	1:30pm	1.04	1.05	1.05
	10:30pm	0.73	0.51	0.52
Gaize	1:30am	1.50	1.02	1.00
	10:30am	0.91	0.81	0.79
	1:30pm	1.02	0.74	0.71
	10:30pm	1.81	0.95	0.94

704

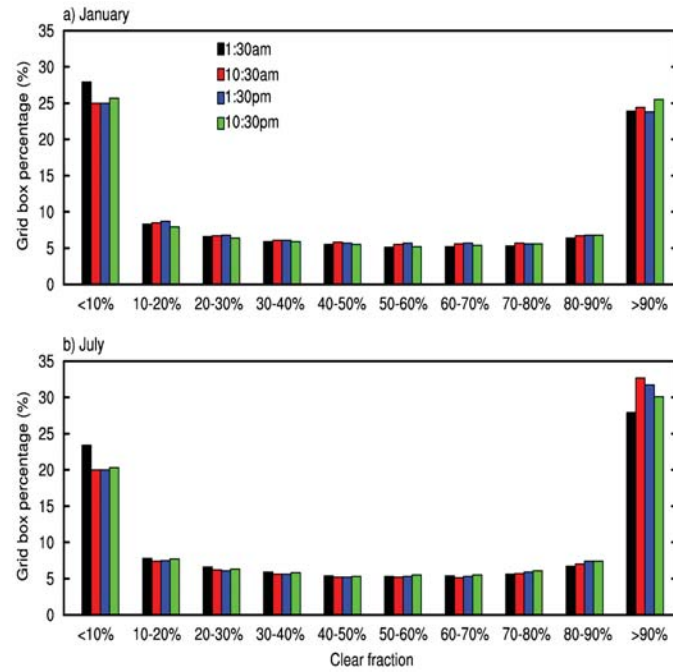
705 Table 4 Monthly Ts differences (K) averaged over Northern Hemisphere (NH) and  
 706 Southern Hemisphere (SH) land grid boxes between CLM-C and MODIS, and  
 707 between CLM-N and MODIS in January and July 2003, respectively. At each MODIS  
 708 satellite overpass time, only the grid boxes meeting two criteria are used to compute  
 709 monthly Ts in CLM: a) bare fraction (BF) is greater than 30%; and b) MODIS  
 710 clear-sky fraction (CF) is greater than 50% for at least 10 days in the month.

711

		SH		NH	
		CLM-C& MOD	CLM-N& MOD	CLM-C& MOD	CLM-N& MOD
January	10:30am	-7.73	-6.31	-6.50	-6.14
	1:30pm	-4.36	-1.98	-2.65	-1.76
July	10:30am	-5.65	-5.27	-5.60	-4.47
	1:30pm	-3.69	-2.86	-0.75	1.25

712

713



714

715 Figure 1. Distribution of global land CLM4.0 grid boxes (excluding the Antarctic) by  
 716 clear-sky fraction, using results from each overpass for each day for the whole month  
 717 in January and July, 2003.

718

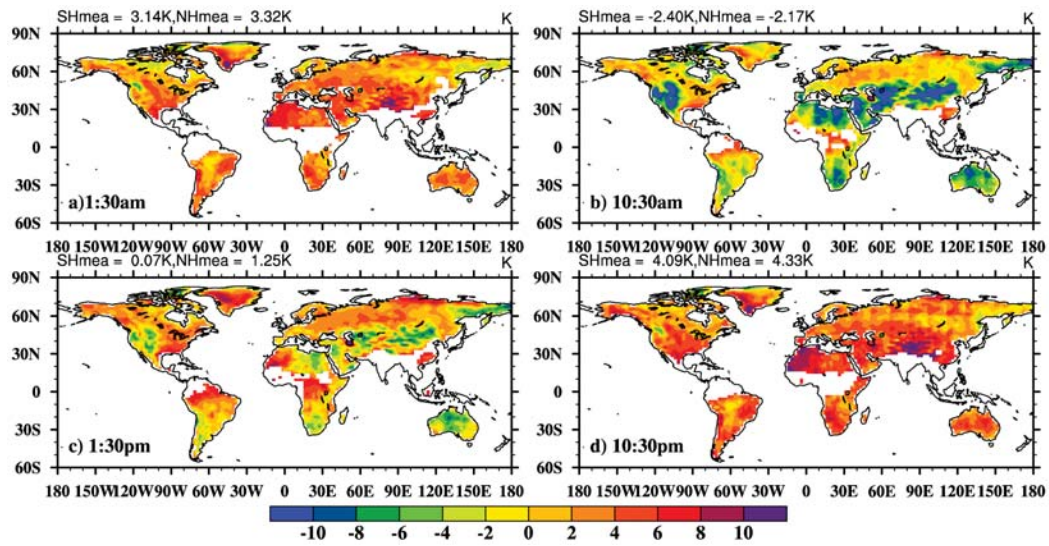


Figure 2. Monthly Ts differences between CLM-C and MODIS at four overpass times in July 2003. At each overpass time, CLM-C monthly Ts values are computed only for grid boxes with MODIS clear-sky fraction > 50% for at least 10 days in the month. The areal weighted values over each hemispheric land areas are also shown in the figure.

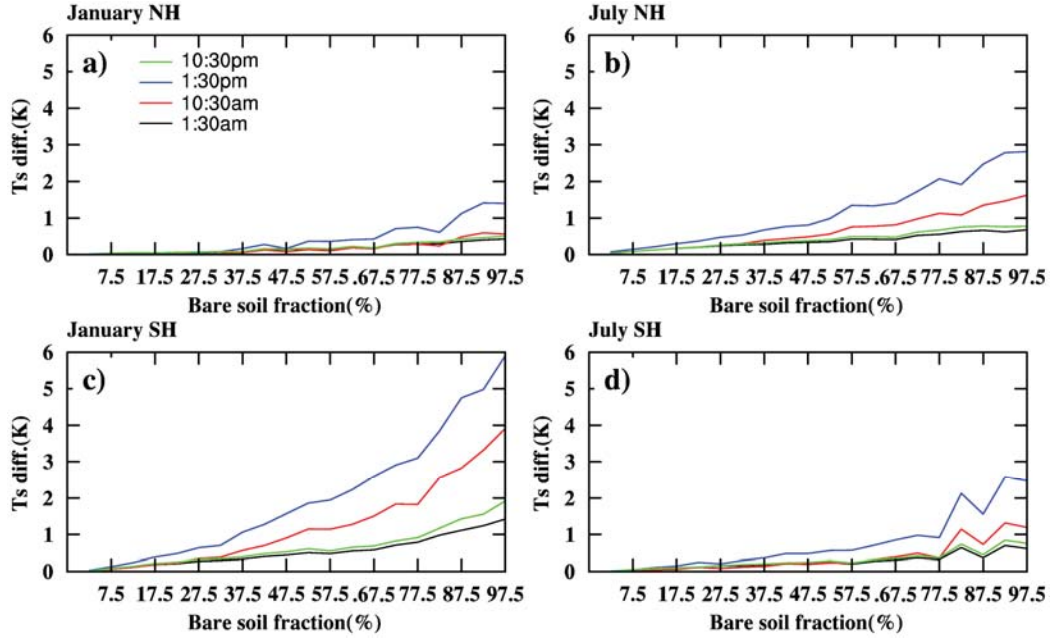
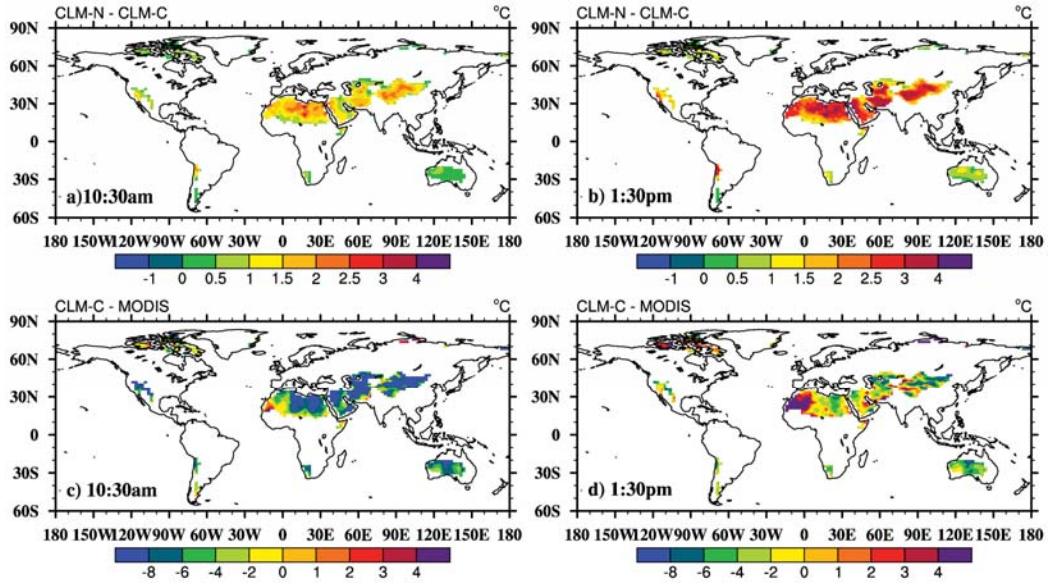


Figure 3. Hemisphere mean Ts differences between CLM-N and CLM-C versus bare soil fraction in 5% intervals at four satellite overpass times averaged in January and July 2003. NH and SH denote Northern and Southern Hemispheres, respectively.

733



734

735

736

737

738

739

740

741

Figure 4. Global distribution of Ts differences between CLM-N and CLM-C at a) 10:30am; b) 1:30pm, and between CLM-C and MODIS at c) 10:30am; d) 1:30pm in July 2003. At each satellite overpass time, monthly Ts is computed over grid boxes with bare soil fraction greater than 30% and MODIS clear-sky fraction greater than 50% for at least 10 days in the month.

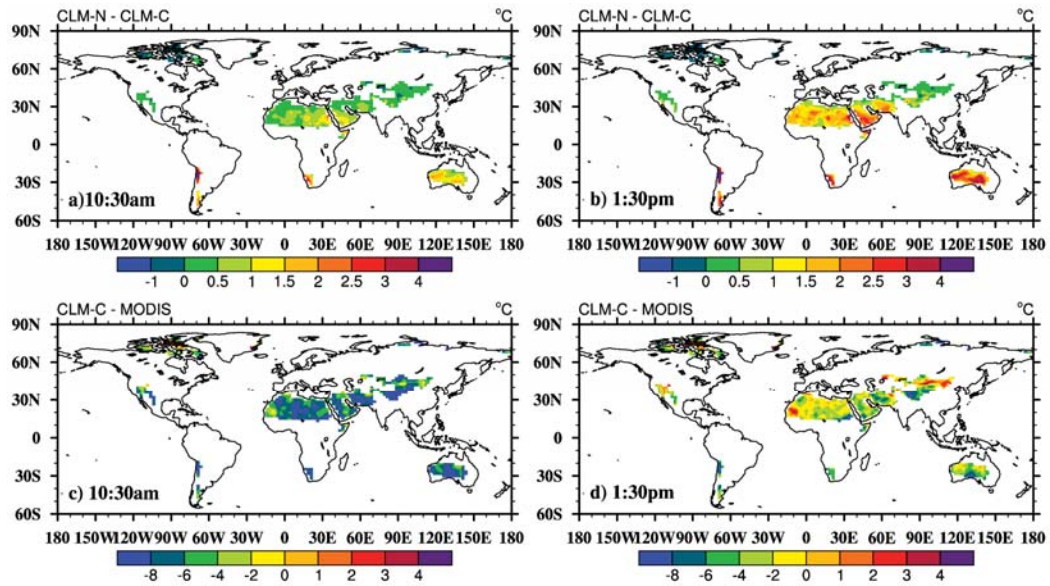


Figure 5. Similar as Figure 4 but for January 2003.



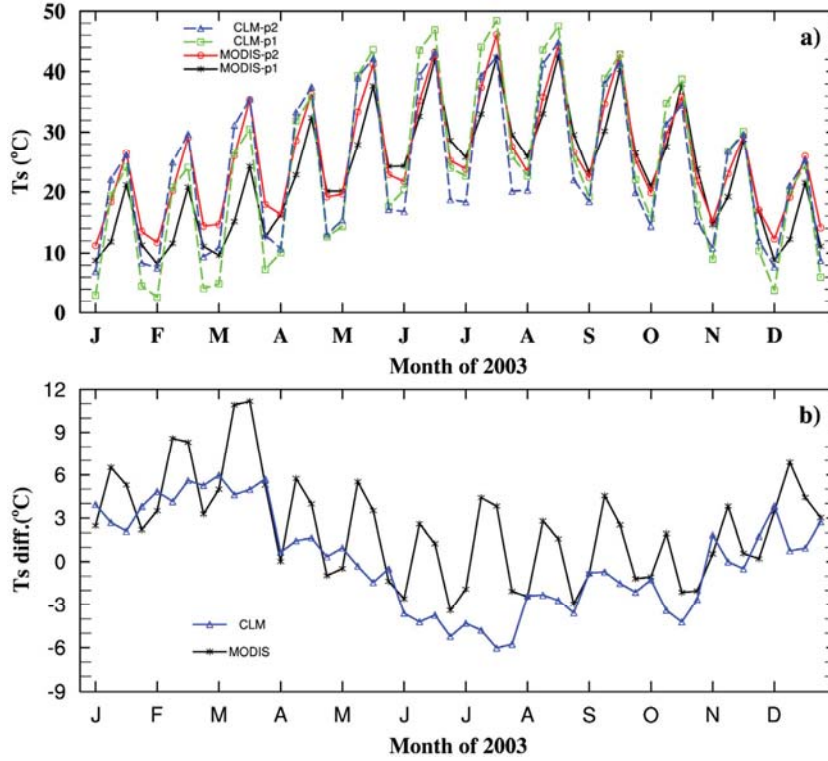


Figure 6. a) Monthly averaged  $T_s$  at two grid boxes at the four satellite overpass times and b) the  $T_s$  differences between these two boxes (centered around  $29^\circ\text{N}/23^\circ\text{E}$  and  $29^\circ\text{N}/10^\circ\text{W}$ ) from CLM-C and MODIS. Both boxes are located in the Sahara Desert with bare soil fraction greater than 90%.